CLIMATE AND THE SLAVE TRADE

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ABSTRACT. African societies exported more slaves in colder years. Lower temperatures reduced mortality and raised agricultural yields, lowering slave supply costs. Our results help explain African participation in the slave trade, which predicts adverse outcomes today. We use an annual panel of African temperatures and port-level slave exports to show that exports declined when local temperatures were warmer than normal. This result is strongest where African ecosystems are least resilient to climate change. Cold weather shocks at the peak of the slave trade predict lower economic activity today. We support our interpretation using the histories of Whydah, Benguela, and Mozambique.

1. INTRODUCTION

One of the key mechanisms through which geography affects modern development is its influence on historical events. Many of the deep roots of economic development have been shaped by the environment, including the timing of the adoption of agriculture (Ashraf and Michalopoulos, 2014), ethnic diversity (Michalopoulos, 2012), and the nature of ethnic institutions (Alsan, 2014). As Nunn (2014) points out, "[t]he impacts of geography depend crucially on the particular historical context." The intersections of the disease environment with the process of European colonization (Acemoglu et al., 2001), droughts with the course of the Mexican revolution (Dell, 2012), and terrain ruggedness with Africa's slave trades (Nunn and Puga, 2012) are all examples of how the environment has shaped present-day outcomes because it has mattered at specific

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moments in the past. In this paper, we show that environmental shocks shaped the dynamics of the transatlantic slave trade. Through the persistent effects of this trade, these past weather conditions continue to influence outcomes in the present.

Our approach is to use reconstructed annual data on African temperatures to measure the year-to-year variation in weather conditions over space during the time of the transatlantic slave trade. We use this data to construct port-specific annual temperature shocks, and combine these with port-level annual slave exports. The panel nature of this data allows us to control both for port-level heterogeneity and for the flexible evolution of the slave trade as a whole over time. We find a considerable decrease in the number of slaves shipped from ports in warmer years. This result is robust to several alternative specifications, including aggregated units of observation, addition of port-specific time trends, and estimation on sub-samples partitioned over time and space. In addition to studying annual temperatures, we also examine the role of longer-term environmental factors by looking at the effect of climate (that is, long-run trends in temperature) on slave exports, and find effects that are the same in sign and much larger in magnitude.[1]

Our interpretation is that warmer temperatures led to increased costs of raiding for slaves. Higher temperatures reduce productivity in tropical agriculture (Kurukulasuriya and Mendelsohn, 2008; Lobell and Field, 2007; Tan and Shibasaki, 2003) and increase mortality (Burgess et al., 2011). In our baseline specification, the decline in slave exports in response to a $1°\mathrm{C}$ temperature increase is roughly 3,000 slaves. This is comparable to the mean of all non-zero port-year observations of slave exports. A one-standard deviation increase in temperature relative to the port mean is a smaller shock, equivalent to $0.16°\mathrm{C}$; the decline in exports in response to this shock is roughly 500 slaves, and is comparable to the mean number of slaves exported across all port-year observations, including zeroes.

We argue that this effect worked through higher costs of collecting taxes and tribute for local states, lower productivity in supporting sectors of the economy, greater disorder in the regions where slaves were usually captured, and higher slave mortality. We show that the effect we find is stronger in Africa's sub-humid and dry savannah regions than it is in areas of moist savannah and humid forest. That is, the regions of Africa in which agricultural productivity is most sensitive to fluctuations in temperature (Seo et al., 2009) were those that responded most in terms of slave exports. Further, we find that both long-run trends in climate and short-run shocks around these trends have power to explain variation in slave exports. We support our interpretation using case studies of three ports that are influential in our results: Benguela, Whydah, and Mozambique. Our results confirm the importance of supply-side environmental factors in accounting for the trans-Atlantic slave trade.

[1]Climate science usually distinguishes between short-run "weather" and long-run "climate." Climate is a statistical description, usually the mean and variability, of relevant quantities over a period of time. As defined by the World Meteorological Organization, this time period is 30 years (IPCC, 2007).

Using modern-day light density at night to proxy for economic activity, we find that the regions around ports that received cold temperature shocks at the peak of the trans-Atlantic slave trade are poorer today. Over the long run, then, the negative impacts of greater participation in the slave trade outweigh the transitory benefits of greater productivity and reduced mortality. The literature on the long run effects of the slave trade has emphasized several channels through which this effect may operate. Many of these are consistent with the data; we show that the incidence of conflict is lower, levels of trust are greater, local and traditional authorities are more responsive, and women's outcomes improve in regions that experienced warm temperatures during the slave trade

1.1. **Contribution.** Our results help explain the relationship between the environment and development. A large literature has emphasized the role of geographic characteristics in shaping economic outcomes in the present, in particular through their impact on institutions (Acemoglu et al., 2012a, 2001). Our results relate past environmental shocks in Africa to its present poverty through the adverse long-run effects of the slave trade.

The unchanging nature of geographic endowments makes it difficult to separate their direct and indirect effects from the impacts of local unobservable variables. Recent work, then, has used natural experiments such as the eradication of endemic diseases (Bleakley, 2007) or variation over time in temperature and rainfall (Brückner and Ciccone, 2011; Dell et al., 2012). Abrupt and persistent changes in climate have precipitated economic collapse through lowered agricultural productivity, depopulation, the decline of cities and the weakening of states (Chaney, 2013; DeMenocal et al., 2001; Diamond, 2005; Haug et al., 2003; Hornbeck, 2012; Weiss and Bradley, 2001). The mechanisms for these effects are not yet fully understood. We give evidence that the impact of temperature shocks on sectors outside of agriculture has not been confined to the industrial era, and we provide one possible mechanism by which temperature shocks affect modern incomes. We show that even small, short-run changes had large impacts on the productive sectors and coping mechanisms of African societies. The slave trade's effects on modern-day institutions, mistrust and poverty in Africa are, then, partly reflections of the continent's environmental history.

We also add to existing knowledge of the economics of conflict. To the extent that current economic growth attenuates the rise of conflict (Collier and Hoeffler, 2004), we contribute to the literature that explains how history matters for modern conflict. Strong correlations between economic shocks, economic grievances, and the onset of conflict have been discussed in the literature (Brückner and Ciccone, 2010; Ciccone, 2011; Miguel et al., 2004). The proposed mechanisms for this link focus on the greater relative returns and lower costs of insurrection during periods of reduced income (Blattman and Miguel, 2010; Chassang and Padró-i Miquel, 2009, 2010).

It is not established that the same relationships have held in the past, nor has it been shown whether endemic, parasitic violence will respond in the same way to economic shocks. Violence in Colombia intensifies when coca or oil prices rise (Angrist and Kugler, 2008; Dube and Vargas, 2013), livestock raiding in Kenya intensifies when herds are healthy (Witsenburg and Adano, 2009), and Japan's long recession has cut into the *yakuza's* profits from racketeering (Hill, 2006, p. 247). The dynamics of the slave trade, then, followed a logic similar to the model of Besley and Persson (2011); greater state revenues encouraged repression (slave raiding) under non-cohesive political institutions. The slave trade is, then, relevant to the broader literature on the roles of institutions and resources in precipitating and perpetuating conflict (Acemoglu et al., 2012b, 2010; Mehlum et al., 2006).

We also contribute to a literature on the economics of the slave trade. The trade intensified internal slavery and lawlessness, and distorted economic and political institutions (Acemoglu and Robinson, 2010). Today, regions that exported more slaves have lower incomes (Nunn, 2008), lower levels of human capital (Obikili, 2013a), are less trusting (Nunn and Wantchekon, 2011), and are more ethnically divided (Whatley and Gillezeau, 2011). Despite the importance of the slave trade, little is known about the influence of African factors on the supply of slaves. Whatley's (2008) paper on the guns-for-slaves cycle is the only empirical study of African supply dynamics of which we are aware.

A more narrow literature in African history has discussed the role of environmental shocks in the slave trade. Historians such as Hartwig (1979) have suggested that droughts and famines may have either increased or decreased the supply of slaves. Lovejoy (2000, p.29,71) argues, for example, that droughts pushed Africans into areas that had been previously depopulated by the slave trade. These individuals then fell victim to slaving once normal conditions resumed. Miller (1982), by contrast, argues that that people, particularly children, were sold into slavery in west-central Africa in order to survive crop failure. For Searing (1993, p.81,83), local food shortages encouraged local slaveowners to sell their slaves to Europeans, but also increased slave mortality. Desert merchants could shut Atlantic merchants out of local grain markets during periods of famine. Crises pushed people to sell themselves or their dependants into slavery, but also led to death and dispersion that reduced the availability of slaves for export and the provisions needed to feed them. Lacking consistent data over time and space, these local qualitative studies have been unable to find the net effect of environmental stress on slave supply. We provide the first such estimates.

We proceed as follows. In section 2, we outline our empirical approach and describe our sources of data on temperature shocks and slave exports. In section 3, we provide our baseline results and demonstrate their statistical robustness. We show that the effect of temperature differs by agro-ecological zone. We decompose the effect of temperature into long-run trends and fluctuations around it. In section 4, we show the impact of past temperature shocks on modern light density and discuss possible mechanisms for this persistence. In section 5, we explain the results. We provide a simple model and argument to account for greater slave exports during years of better agricultural productivity and lower mortality. We discuss evidence from the secondary literature that connects warmer temperatures to increased mortality and reduced agricultural productivity. We support our interpretation by examining case studies of three important slave ports – Whydah, Benguela, and Mozambique. Section 6 concludes.

2. EMPIRICAL STRATEGY AND DATA

2.1. **Empirical strategy.** Our data will consist of a panel of annual slave exports and temperatures for 134 ports that were engaged in the trans-Atlantic slave trade. The dependent variable of interest, the number of slaves exported from port i in year t, is bounded below by 0. Thus, our main specification is the following:

$$slaves_{i,t} = max(0, \alpha + \beta\, temperature_{i,t} + \delta_i + \eta_t + \epsilon_{i,t}) \tag{1}$$

Here, $slaves_{i,t}$ is number of slaves exported from port i in year t. $temperature_{i,t}$ is the temperature at port i in year t, δ_i is a port-level fixed effect, η_t is a year fixed effect and ϵ_{it} is the error term. We estimate (1) using a tobit estimator.[2] We use ports as the unit of observation because this is the finest geographical level at which the data on slave exports are available; we show in section 3.3 that we can find similar results using alternative units of observation.

Standard errors are clustered by the nearest grid point in our temperature data, since there are fewer grid points than there are ports. To further address serial correlation over time or space, we also report standard errors clustered by year, by unique port locations, by $1^\circ \times 1^\circ$ squares, and by $2^\circ \times 2^\circ$ squares. In the online appendix (Table A0), we show that if we use ordinary least squares to estimate (1), the standard errors do not grow appreciably as these squares are made larger, using conventional or Cameron et al. (2008) standard errors. They are also similar in the linear model when Cameron et al. (2008) standard errors are used to cluster by both $1^\circ \times 1^\circ$ square and year at once.

In addition to using temperature as the key explanatory variable of interest, we also estimate the impacts of the long-run moving average (climate) and the variation of temperature around this average (climate shocks) on the supply of slaves.

2.2. **Data.**

2.2.1. *Temperature.* In order to estimate (1), we use three principal sources of data. The first covers temperature. The historical data are reported as temperature "anomalies," and are taken from Mann et al. (1998a,b). They reconstruct annual temperature anomalies using multivariate calibration on a 5° by 5° grid. They combine data from several

[2] In a linear fixed effects model, the impact of annual temperature shocks and that of annual temperature would be identical, since the long-term mean temperatures would be collinear with the port fixed effect. While this is not true in the case of a tobit estimator, the magnitude of the impact of temperature shocks and temperature are nearly identical.

previous paleoclimatic studies that calculated historical temperatures using data from different proxy indicators. These include coral, ice cores, tree rings, and other long instrumental records. The availability of multiple indicators increases the robustness of the estimates, and their calculations account for the appropriate potential limitations of each proxy indicator. They calibrate the proxy dataset using monthly instrumental data from 1920-1995, and compute annual temperature anomalies for each year from 1730 to 1900 relative to the baseline average temperature during the period 1902 to 1980. A more detailed overview of the data is presented in online appendix C, and additional details of their methodology are available in Mann et al. (1998a,b). The dataset has been used by numerous climate scientists to study long-term climate warming trends (Covey et al., 2003; Crowley, 2000; Huang et al., 2000).

A temperature anomaly of $1°\mathrm{C}$ at port i in year t means that the temperature at i was $1°\mathrm{C}$ higher during t than the mean temperature at i over the period 1902-1980. We reconstruct the baseline temperatures for each port using a separate temperature series from the University of Delaware, which covers the 1902-1980 period. This permits us to convert the anomalies into an annual temperature series for each port.[3] There is considerable variation in temperature across years for each port, and shocks within a single year vary across ports. In the online appendix, we present the time series of temperature shocks for two of our case studies: Benguela and Whydah. In more than 30% of the years in our data, one of these ports is experiencing a shock above its long-run mean while the other is experiencing the opposite.

In addition to using these temperatures directly, we convert them into fluctuations around longer-run climate trends by removing the 30-year running mean from each port. These are then treated as shocks over and above the long-term trend in climate. In our analysis, we also use this running mean of climate as a regressor to estimate the impact of changes in longer-run climate on the dynamics of the slave trade. Where data are missing on the 5° by 5° grid, we impute anomalies separately for each year using a cubic polynomial in latitude and longitude, with full interactions. Because our data are annual, we are unable to isolate temperature shocks during critical months in the agricultural calendar. This attenuation bias will push our results towards zero.

We have used the temperature series from Mann et al. (1998a), rather than the updated series from Mann et al. (2009) for our analysis. This is because the revised series is smoothed and is highly persistent over time for individual ports. This creates an unrealistic absence of year-to-year variation in temperature and introduces substantial serial correlation. Although temperature residuals after port and year fixed effects are

[3]Baseline temperatures can be downloaded from `http://climate.geog.udel.edu/~climate/html_pages/download.html#P2009`. We originally downloaded the historical anomalies from `http://picasso.ngdc.noaa.gov/paleo/data/mann/`. These have since been moved to `http://www.ncdc.noaa.gov/paleo/pubs/mann1998/frames.htm`, and we are willing to provide the data on request. Vlassopoulos et al. (2009) have used these data previously.

removed from the Mann et al. (1998a) and Mann et al. (2009) series are positively correlated, the partial R-squared of this correlation is less than 0.01. As a result, the Mann et al. (2009) data provide similar coefficient estimates but much larger standard errors than the Mann et al. (1998a) data in our main results, results by agro-ecological zone, and results for climate trends. For example, our baseline estimate of β in (1) is -3,052 using the Mann et al. (1998a) and -2,594 using the Mann et al. (2009) revisions. However, the standard error rises from 1,115 to 2,463.

2.2.2. *Slave exports.* The second source of data that we use is the Trans-Atlantic Slave Trade Database of Eltis et al. (1999).[4] The trans-Atlantic slave trade, which is the focus of this study, comprised roughly two thirds of the volume of slaves transported from Africa between 1400 and 1900 (Nunn, 2008). Because the temperature data are only available after 1730, we are confined to analyzing the impact on the slave trade during this period. Since the overwhelming bulk of slaves were shipped across the Atlantic in this period, we are able to study the slave trade when it was at its most active. The database provides voyage-level data on more than 34,000 voyages, including information on the number of slaves carried, the year the ship departed Africa, and the principal port of slave purchase, which is the port where the largest number of captives embarked.

We convert these raw data into an annual port-level panel. Since not all ships embarked from known ports or, in some cases, known regions, this requires assigning several of the slaves to ports. 60% of slaves come from ports with known latitude-longitude coordinates. 20% come from a known region (such as the Bight of Benin) but with no port given in the raw data. 20% come from voyages in which only the year is known.[5] We assign slaves from ships from known regions and unknown ports in proportion to the number of slaves that are exported from the known ports within that region in a given year. Analogously, we assign slaves from ships from unknown regions and unknown ports in proportion to the number of slaves that are exported from all known ports within a given year. We obtain a panel of 134 ports spanning 137 years, from 1730 to 1866.

Temperature shocks for each port are computed by taking the four nearest points in the temperature data and interpolating bilinearly.[6] We treat these as proxies for conditions within the catchment zone of each port, since the vast majority of slaves came from areas within 100 miles of the coast (Evans and Richardson, 1995, p. 675), even though slaving frontiers did expand inland over time (Miller, 1996). Similarly, the estimates in Nunn and Wantchekon (2011) suggest that roughly 90% of slave exports came from ethnic groups with centroids within 500km of the coast (see Figure A.1 in online appendix D).

[4]The database is online, at `http://www.slavevoyages.org`.

[5]Fewer than 1% of slaves in the data come from ports to which we have been unable to assign geographic coordinates. We treat these ports as observations with a known region, but no known port.

[6]There is no noticeable difference in the magnitude or variance of temperature shocks for the points over water relative to the points over land, and so we do not treat them differently.

We map both the temperature points for which Mann et al. (1998a) report their data and the ports reported in the Trans-Atlantic Slave Trade Database in Figure 1. Summary statistics for our sample are given in Table 1. A kernel density plot of slave exports is included in online appendix F. The mean number of slaves exported annually per port is close to 450, and increases to roughly 2,500 when we only consider ports that exported a non-zero number of slaves in a given year. The standard deviation reported in the table conflates differences in temperatures across ports with within-port variation. The standard deviation of temperature with port means removed is roughly $0.16°\mathrm{C}$.

2.2.3. *Agro-ecological zones.* The third source of data is on agro-ecological zones (AEZs). These data classify land into zones based on climate, elevation, soils and latitude, and are compiled by the Food and Agriculture Organization (FAO). The original AEZ classification classifies land in Africa into 16 zones, which includes five climatic zones each at three levels of elevation (high, medium and low), and the desert. These AEZs are stable across time, since they are classified using factors such as long-term climate, soil, elevation and latitude. To estimate the effects of temperature separately by AEZ, we collapse the same ecological zone at each elevation into a single classification. For instance, we classify high-elevation dry savannah, mid-elevation dry savannah and low-elevation dry savannah all as "dry savannah". Ports are assigned the AEZ of the nearest African administrative unit in the data used by Kala et al. (2012). The 134 ports in our data comprise desert, dry savannah, moist savannah, sub-humid, and humid forest zones.

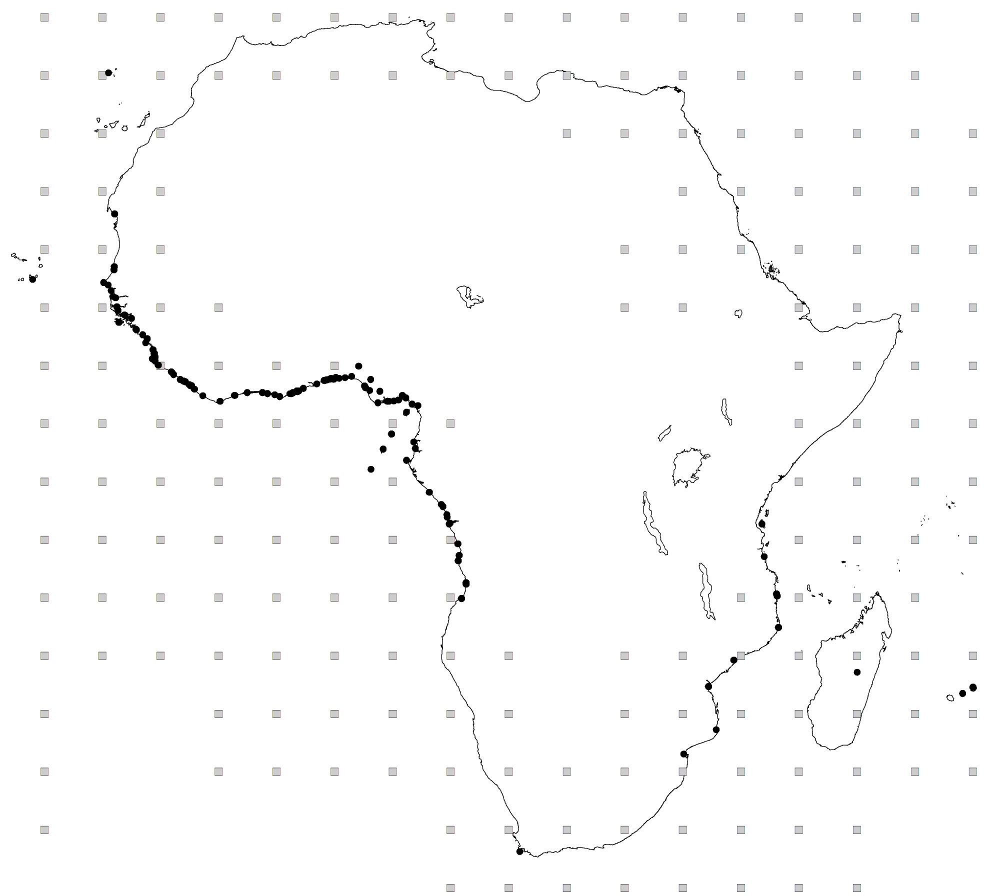
3. Results

3.1. **Main results.** We present our main results in Table 2. We find that a one degree increase in temperature leads to a one-year drop of roughly 3,000 slaves from the treated port. This is a sizeable effect, roughly equal to the mean for a port whose exports are nonzero in a given year. For a one standard deviation increase in de-meaned temperature (roughly $0.16°\mathrm{C}$), the effect would be about 480 slaves.[7] This is roughly a one quarter of a standard deviation movement in slave exports.

Scientific evidence indicates that the process of multi-proxy historical temperature reconstruction may create a temperature series with dampened variability (Christiansen and Ljungqvist, 2011; Riedwyl et al., 2009; von Storch et al., 2004). This dampening would scale up our estimated coefficient. In the baseline period 1902-80, the port-specific temperature anomalies have a standard deviation of $0.42°\mathrm{C}$. If our historical temperature data have been dampened by the ratio $0.16/0.42$, then our coefficient estimates should be re-scaled by this same ratio. This gives a slave supply response to a $1°\mathrm{C}$

[7]This is smaller than the standard deviation reported in Table 1, since that figure reflects variations in temperature across ports, rather than fluctuations experienced by individual ports over time.

FIGURE 1. Map of ports and temperature points



The black circles are the ports that appear in the Trans-Atlantic Slave Trade Database. The grey squares are the points of the 5° by 5° grid on which Mann et al. (1998a) record temperature anomalies.

temperature shock of roughly 1,200 fewer slaves. This is approximately a two thirds of a standard deviation reduction in slave exports.[8]

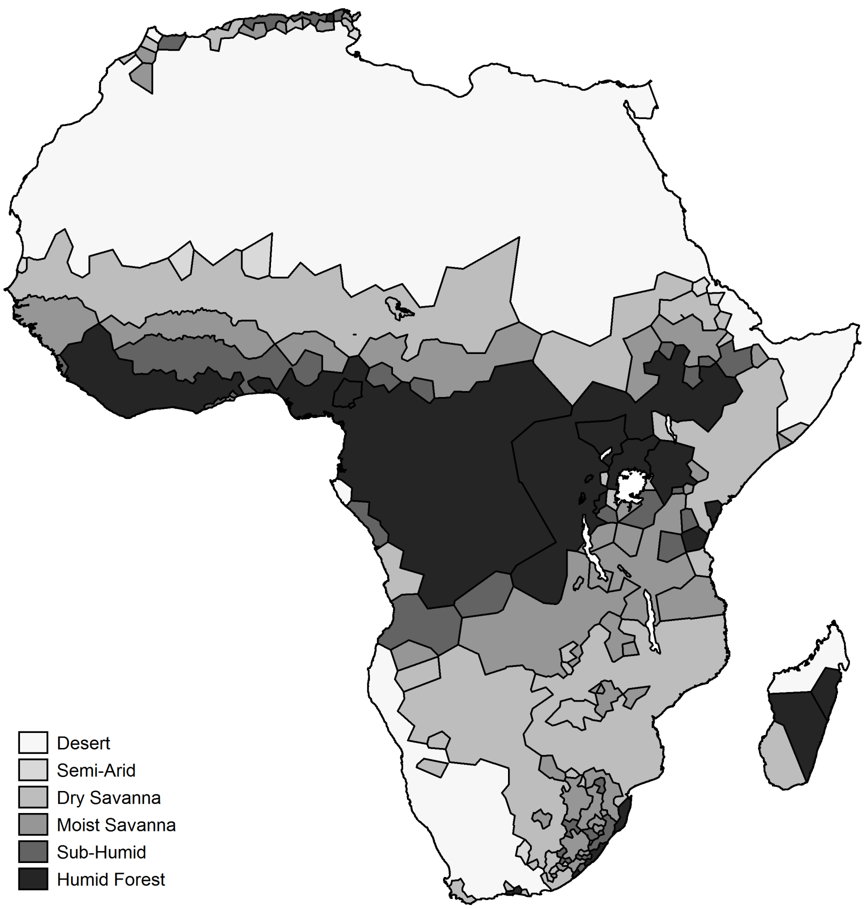
Though this magnitude may appear large, a one-degree higher temperature over an entire year is a significant shock. Dell et al. (2012) show that a one degree temperature increase in the present day is associated with lower economic growth by about 1.3

[8]While it is possible that temperature has non-linear impacts on slave exports, the linear relationship is a good approximation of this effect. One of our primary proposed mechanisms is the link between temperature and agricultural productivity, discussed in section 3.2. Studies of this relationship in Africa find small and often insignificant effects of higher-order polynomial terms in temperature (Kurukulasuriya et al., 2011; Kurukulasuriya and Mendelsohn, 2008). Further, studies linking temperature to economic outcomes generally rely on linear specifications (Burgess et al., 2011; Dell et al., 2012). If we include a quadratic term for temperature, we find that the marginal effect is smaller at greater temperatures, diminishing from roughly $-5,000$ at $20°C$ to roughly $-2,600$ at $25°C$ (not reported). Interacting temperature shocks with mean temperature shows a similar pattern: the effect of a $1°$ shock is weaker at warmer ports (not reported).

percentage points in poorer countries, and impacts both the agricultural and industrial sectors.

3.2. **Mechanisms.**

FIGURE 2. Map of agro-ecological zones



Point data on agro-ecological zones are taken from Kala et al. (2012) and converted to polygons by constructing Thiessen polygons around each point.

3.2.1. *Results by ecological zone, crop, and region.* In Table 3, we show the results differ across African agro-ecological zones (AEZs). We map these AEZs in Figure 2. The general pattern that emerges is that the elasticity of slave exports with respect to temperature is greater in drier environments. These results suggest that agricultural productivity was an important channel, since these are the regions in which agriculture would be most sensitive to fluctuations in weather (Seo et al., 2009). The largest impact is on dry savannah and deserts followed by sub-humid zones, and the lowest impacts are on moist savannah and humid forest. p-values for the equality of coefficients across AEZs are presented in the online appendix, in Table A3. We also interact temperature with an indicator for humidity above the median in this table.[9] The interaction is significant; above-median humidity completely attenuates the effect of temperature.

What drives these interactions? Kala et al. (2012) analyze current agricultural productivity by AEZ, and find that moist savannah and sub-humid zones, where the impacts of temperature on slave exports are relatively minor, are more productive in general than dry savannah zones. At high and mid-elevations, sub-humid zones can have productivity similar to (or even greater than) that of moist savannahs. This helps explain why both have intermediate coefficients between the large impact on dry savannah and the negligible impact on humid forest. Other analyses of ecological zones in Africa find that the growing season is longer in sub-humid and humid zones than in semi-arid and arid zones (Bationo et al., 1998). Plant growth potential is also higher in sub-humid and humid areas (Ojwang et al., 2010). Both tendencies make these areas less vulnerable to shocks.

Higher temperatures are more likely to exacerbate the disease burdens of malaria and trypanosomiasis in humid regions (Munang'andu et al., 2012; Yé et al., 2007), but we see larger impacts of higher temperatures in dry ecological zones. Thus, while the heterogeneous effects of temperature across AEZs are unlikely to be explained by its impact on the disease burden, it may increase mortality by operating through the agricultural channel. That is, since warmer years are years of lower agricultural productivity, they may also be years of higher mortality due to food scarcity. Thus, agricultural productivity could directly affect the costs of raiding as we discuss below, or indirectly affect it through the channel of increased mortality.

These differences in AEZs overlap with differences in cropping patterns and with the broad regions of the slave trade. In Table 3, we show that regions that cultivated cereal grains experienced the largest declines of slave exports in response to a temperature shock, followed by those that cultivated roots and tubers. The effects of temperature are insignificant for areas where agriculture was unimportant.[10] These results have a similar interpretation to the heterogeneous effects by AEZ. Cereal grains are more vulnerable to climate change than roots and tubers (Lobell et al., 2008). Tree crops' longer roots make them better at nutrient uptake, and less responsive to a single year of weather variability (Nguyen et al., 2012). Furthermore, tree crops such as oil palm and coconut are very resilient to heat stress, particularly short-lived heat stress, whereas popular tuber crops such as cassava, yam and sweet potato are only moderately heat-tolerant (Hartley, 1967; Kuo et al., 1993; Onwueme and Charles, 1994; Yamada et al., 1996). There is no evidence here that African societies chose more durable crop types in drier AEZs. Cereal grains, for example, are dominant in both dry and moist savannah, while roots and tubers are most important in both sub-humid zones and humid forest.

[9]Humidity data are from `http://en.openei.org/datasets/node/616`

[10]We use the Murdock (1967) *Ethnographic Atlas* to identify the prevalent crop for each port. Each society's dominant crop type is given by variable $V29$. We take the modal crop for all societies within 500km of each port. If there are no societies within 500km, we use the nearest society in the *Atlas*.

We also use Table 3 to show that broad differences exist across the major regions of the slave trade. The negative effects of temperature that we find are confined to Senegambia, the Bight of Benin, West-Central Africa, and Southeastern Africa. Some of the effect size for West-Central and Southeastern Africa can be accounted for by their overwhelming preponderance in the slave trade. Nunn (2008) estimates that Angola alone sent more than three and a half million slaves across the Atlantic between 1400 and 1900. Consistent with our results by AEZ, all four of these regions include substantial portions outside Africa's humid forest zone. Senegambia, West-Central and Southeastern Africa all contain substantial portions of savanna and grassland, while in the "Benin Gap," the tropical forest opens and the savanna reaches the coast.

Together, these results suggest that the effects of temperature shocks on the slave trade operated directly and indirectly through agricultural productivity, and were most deeply felt in the parts of Africa with the least resilient ecosystems.

3.2.2. *Climate.* In Table 4, we show that both the thirty-year moving average of temperature and fluctuations around it can explain slave exports. Both coefficients have negative signs. Warmer trends and unusually warm years reduce slave exports. A one degree anomaly over the 30-year climate mean has an average impact of nearly 1,300 fewer slave exports per port per year, similar to our main temperature measure, whereas a one degree increase in the 30-year climate mean has an average impact of nearly 18,000 fewer slave exports per port per year. The impact of a warm trend is much larger than an unusually warm single year. A one standard deviation change in within-port climate causes about 1,800 fewer slaves to be exported per port per year on average.

Part of this difference may be purely mechanical. The within-port variance of the temperature anomalies is greater than that of the climate anomalies, and the trend for climate will smooth out year-to-year measurement error in temperature. However, the greater impact of a warming trend is also consistent with the mechanisms through which we argue that environmental factors affected the slave trade. The cumulative impact of a warming trend on agricultural productivity and mortality are greater than for a single warm year. Over time, these will lead to depopulation and out-migration, making slave exports increasingly unviable. Though societies may adapt to sustained climate change, a prolonged period of worsening climate can lead to social collapse (DeMenocal et al., 2001; Haug et al., 2003).

As an alternative to using the 30-year mean as a measure of "climate," we also use a Baxter and King (1999) bandpass filter to decompose temperature into trends and cycles. Following their recommendations, we set the minimum period of oscillation to 2, the maximum period of oscillation to 8, and the lead-lag length of the filter to 3. We report results in Table 4. Using these measures, trends have the power to predict slave exports, but shocks around them do not. This difference is not surprising, since the trend computed using a bandpass filter is more sensitive to annual fluctuations in temperature.

3.2.3. *Other possible mechanisms.* Higher temperatures directly reduce agricultural productivity in Africa. In addition, they predict lower rainfall, which we are unable to observe during the time period covered by our data. Our result, then, mixes the direct impact of temperature with indirect effects that operate through rainfall. To establish the size of the correlation between temperature and rainfall, we use data on temperature and precipitation from the University of Delaware.[11] These report annual temperature and precipitation figures for points spaced every 0.5° by 0.5° from 1900 to the present. We confine our analysis to points in Africa during the years 1900-2000. We regress the log of annual rainfall on the log of annual temperature, point fixed effects and year fixed effects. We find that a one percent temperature increase is associated with lower rainfall of 1.26 percent, with a standard error of 0.028. Though this is a large elasticity, temperature shocks explain less than 1% of the variance in rainfall fluctuations.[12] While our main result captures the combination of higher temperatures and lower rainfall on the supply of slaves, this suggests that the direct effect of temperature on agriculture and mortality is what drives our results.[13]

An alternative reading of our results would infer that higher temperatures were associated with greater natural hazards for transatlantic shippers, and that our results do not reflect "supply side" shocks within Africa. As evidence against this interpretation, we make use of additional data from the Trans-Atlantic Slave Trade Database. For 18,942 voyages that have a known year of travel and a known region or port of slave purchase, the data also record whether the journey was completed successfully, failed due to a human hazard, or failed due to a natural hazard. In this sample, we regress the occurrence of a natural hazard on temperature, port fixed effects, and year fixed effects. To compute a temperature for ships without known ports, we assign ships to the modal port

[11]These are available at `http://climate.geog.udel.edu/~climate/`.

[12]To show this, we begin by running the regression:

$$\ln(Rainfall_{it}) = \delta_i + \eta_t + \epsilon_{it}^R$$

Here, $Rainfall_{it}$ is the level of rainfall at point i in year t. δ_i is a point fixed effect. η_t is a year fixed effect. We save the residuals from this regression. Call these $\hat{\epsilon_{it}^R}$. We treat these residuals as "rainfall shocks". We then run the regression:

$$\ln(Temperature_{it}) = \delta_i + \eta_t + \epsilon_{it}^T$$

Here, $Temperature_{it}$ is the temperature at point i in year t. Fixed effects are as defined above. We save the residuals from this regression. Call these $\hat{\epsilon_{it}^T}$. We treat these residuals as "temperature shocks." We then run the regression:

$$\hat{\epsilon_{it}^T} = \beta_0 + \beta_1 \hat{\epsilon_{it}^R} + \varepsilon_{it}$$

The R-squared of this regression is less than 0.01, suggesting that rainfall shocks only explain a small fraction of the variance of temperature shocks. These shocks are correlated, but they do not move in lock-step. There is no justification for treating temperature as a proxy for drought alone.

[13]We have also performed this same regression using levels, rather than logs, and using binary indicators for whether rainfall or temperature are above their historical means. Both of these give results consistent with the log specification.

in the region of slave purchase. We find that a $1°C$ temperature increase reduces the probability of a natural hazard by 10.4 percentage points, with a standard error of 3.5 percentage points. Warmer years were associated with fewer natural hazards for those who shipped slaves across the Atlantic. Our main result works in the opposite direction, and overcomes this effect.

A third alternative explanation for our results is that wind speeds were higher in colder years, which enabled ships to make a greater number of voyages than in warmer years. There are several reasons why this is not a main driver of our results. First, as discussed in section 3.2.1, the impacts of temperature are heterogenous by agro-ecological zone, which would not be the case if the results were driven by lower temperatures enabling the ships to complete more voyages due to increased ship speeds.

Second, we use modern data on temperature and wind speed to show that higher temperatures only lead to small declines in wind speeds in the present. We use modern day (1950-2000) temperature and wind speed data from the Laboratoire de Météorologie Dynamique.[14] We regress annual wind speed on annual temperature, controlling for year and point fixed effects. A one degree Celsius increase in temperature leads to a 0.01 meters/second (m/s) increase in wind speed globally, and a -0.02 m/s decrease in wind speed in the geographic region in Africa. These effects are quite small relative to the mean wind speed, which is 3.2 m/s at the global level and 2.99 m/s around the region near Africa. Even though there is a negative association between temperature and wind speed in and around Africa, the magnitude is only about 1% of the mean, and it explains very little of the variation in wind speeds.[15]

It is also unlikely that voyage lengths are driving our result. Shippers had limited scope to lengthen their buying periods in response to diminished African supply. Because labor and borrowing costs increased with the length of a voyage, European traders were keen to minimize their time on the African coast (Miller, 1996, p. 327). Miller (1981, p. 414) estimates that slaves in eighteenth-century Angola typically waited one month in barracoons at the coast before being loaded onto a slave ship. Searing (1993, p. 80) similarly notes that shippers attempted to avoid risk and economize on feeding costs by minimizing the time between purchase and shipment. Harms (2008) describes the 1731 voyage of *The Diligent*, a French slaving vessel. On several occasions, the ship left a West African port without purchasing slaves because the asking price was too high or because slaves would only be available after a delay.[16] Of the voyages for which the time between departure from home port and departure from Africa are known, fewer than 10% spent longer than one year in Africa. A kernel density of this distribution is reported in online appendix F.

[14]A detailed explanation of the data and the analysis is available in online appendix B.

[15]That is, regressing the partial residuals from a regression of wind speed on the point and year fixed effects on the partial residuals from a regression of temperature on these same fixed effects gives an R-squared of 0.003.

[16]See Harms (2008), pages 143, 148, 151, 152, and 212.

Another alternate interpretation of our findings would link higher temperatures with greater productivity in cattle-keeping. In humid forest regions, higher temperatures increase the prevalence of tsetse flies, which increases morbidity and mortality of both men and cattle, due to the spread of sleeping sicknesses. In drier zones, however, higher temperatures kill the tsetse, benefitting cattle production (Pollock, 1982). We use three tests to show that this mechanism does not explain our results. First, we use the Murdock (1967) *Ethnographic Atlas* to identify the percentage of societies within 500km of each port who possess bovine animals.[17] Including the interaction between temperature and average bovine presence does not diminish the main effect (see Table A1, in the online appendix). The interaction effect is positive, suggesting that the effect of temperature is in fact *weaker* in areas that keep cattle.

Similarly, we use the *Ethnographic Atlas* to calculate the average dependence on animal husbandry for the societies within 500km of each port.[18] Including the interaction between temperature and dependence on husbandry again does not diminish the main effect (Table A1). The interaction is positive, but not significant. Third, we include the interaction between temperature and the suitability of the area within 500km of each port for tsetse.[19] Yet again, this does not diminish the main effect (Table A1). The interaction is positive, but not significant.

3.3. **Robustness.** We have tested the robustness of our main result to multiple checks for unobserved heterogeneity, measurement of slave exports and temperature shocks, the unit of observation, outliers, the estimation method, and the inclusion of lag slave exports as a control. The results of these tests are presented in the online appendix. In some specifications, we were unable to compute clustered standard errors using temperatures, and so anomalies (with nearly identical point estimates) were used in their place. These are indicated in the tables.

3.3.1. *Heterogeneity.* To account for port-specific heterogeneity, we have allowed for port-specific linear trends and region-specific quadratic trends.[20] These results are reported in Table A1. The addition of port and region-specific trends allow the right hand variables to evolve flexibly over time within a port or region.[21] We also estimate (1) on the sub-samples before and after the British abolition of the slave trade in 1807. This

[17]We use the latitude-longitude coordinates provided in the *Atlas* to identify the locations of these ethnic groups. The presence of bovine animals is an indicator equal to 1 if variable $V40$ is equal to 7, if $V40$ is non-missing. If there are no societies within 500km, we use the nearest society in the *Atlas*.

[18]Dependence on husbandry is variable $V4$. If there are no societies within 500km, we use the nearest society in the *Atlas*.

[19]Tsetse suitability is raster data downloaded from `http://ergodd.zoo.ox.ac.uk/paatdown/index.htm`. This is only available for mainland Africa, and so these regressions exclude Madagascar and ports more than 500km from the mainland.

[20]Convergence could not be achieved with port-specific quadratic trends using the tobit estimator. If these are included in an OLS estimation, the impact of temperature on slave exports remains negative and significant.

[21]In particular, they remove the need to include the interaction of the right-hand side variables by year.

shows both that a major break in the demand structure of the slave trade does not affect the supply-side link between temperature and slave exports, and that the results survive despite the relatively poor data available for individual ships after 1807.[22] Similarly, discarding the years of the US Civil War does not meaningfully change the results.

Estimating the results separately for every 25-year interval in the data, we find a negative coefficient in more than 90% of intervals. It is significant at the 5% level during the intervals centered from 1752-57, 1781-90, and 1835-1853. We find no evidence that the effect of temperature differed during years with El Niño events.[23] We find no evidence that the effect of temperature varies according to whether shocks are positive or negative relative to the port-specific mean over the 1730-1866 period (Table A1). This is consistent with present-day studies of African agriculture, which find that yields are declining in temperature, rather than being adversely affected by both warm and cold shocks (Exenberger and Pondorfer, 2011; Lobell et al., 2011).

We cannot estimate the effect of demand shifts in the slave trade as a whole, since these are collinear with the year fixed effects used in our principal specification. We can, however, account for port-specific changes in demand by destination region by including the temperature shock experienced at the nearest new world slave port. These ports are, as in Nunn (2008), Virginia, Havana, Haiti, Kingston, Dominica, Martinique, Guyana, Salvador, and Rio. Similarly, we show that the results are robust to including slave prices, both in the embarkation region and in the nearest new world port.[24] Alternatively, we use the disembarkation ports listed in the Trans-Atlantic Slave Trade Database to create a modal destination for each African port. Controlling for the anomaly at these modal destinations also does not change the result. The correlation coefficients of own and New World temperature anomalies, net of year and port fixed effects, are 0.0905 for the nearest New World port and 0.0544 for the modal destination. Both are significant at the 1% level.

Controlling for the 30-year climate trend at the modal destination causes the coefficient on temperature to fall by roughly 15%, though it remains significant. The coefficient remains similar if we include temperature shocks experienced by the major slave-trading powers as controls. We compute these shocks by assigning each African port to the country whose merchants shipped the greatest number of slaves from that port. We

[22] We discuss missing data in greater detail in online appendix A.

[23] We identify El Niño events using the list provided by `https://sites.google.com/site/medievalwarmperiod/Home/historic-el-nino-events`. This list uses Couper-Johnston (2000) as its principal source.

[24] Prices in Africa and the new world are taken from Eltis and Richardson (2004) and cover the years 1671-1810. There are many gaps in these series, especially for the New World ports. These are interpolated linearly using the values of the non-missing prices. For example, gaps in the prices of Senegambian slaves are imputed from the prices in the other African regions. The prices in Eltis and Richardson (2004) are reported for five year intervals. We treat prices as constant within these intervals. The impact of prices themselves in the regression is not statistically significant. The interpolation of prices within years as well as across regions implies that by construction, their ability to reflect the impact of a localized shock in a particular year is limited.

then compute a temperature shock for the major port of that country – Copenhagen, Nantes, Bristol, Amsterdam, Lisbon, Seville, or Virginia. The effect becomes larger in magnitude and remains significant if we also control for the temperature shock at each port's nearest neighbor. The neighbor's shock enters positively, suggesting diversion across ports.[25]

We have also tested for several heterogeneous effects that we do not report. Interacting temperature shocks with mean slave exports gives suggestive evidence that the effect is larger for more important ports, but this interaction term is marginally insignificant. We find no evidence in the cross-section of ports that a greater overall variance of temperature shocks predicts greater average slave exports. We interact temperature with quintiles of terrain ruggedness. The effect is negative and significant in all interactions, and largest in the first and fifth quintiles. We find no heterogeneous effect by malaria suitability. Finally, we do not find heterogeneous effects of temperature that vary by the mean level of state centralization of the societies within 500km of each port recorded in the *Ethnographic Atlas*.[26]

3.3.2. *Measurement.* We show that the method used to assign slaves to ports is not driving the results. We use only the slaves from known ports to calculate port-by-year exports, and achieve similar results to our baseline approach. The effect is smaller, but in proportion to the smaller standard deviation of the dependent variable. The results also survive when using slaves from known ports or regions only. Results are similar if we use slaves disembarked in the new world, rather than slaves embarked from Africa. Results remain negative and significant if slave exports are normalized by the population density of the area within 500 km of each port in 1700.[27]

Similarly, we show that our results are not an artefact of the bilinear interpolation used to construct port-specific temperatures. We can use the temperature calculated from the closest point in the temperature data and achieve similar results to our baseline. We receive very similar results if we discard temperature points located over the ocean when joining ports to their nearest temperature point. We use the natural log of temperature as an alternative measure of weather shocks, in order to account for possibly multiplicative measurement error. The result is still negative and significant. It is also negative and significant if the log of (one plus) slave exports is used as the dependent variable.

[25]Although ports are typically close to their nearest neighbors ($mean = 75.5km$) some are more distant ($s.d. = 203km$, $max = 1,643km$).

[26]This is variable $V33$, if $V33$ is non-missing. If there are no societies within 500km, we use the nearest society in the *Atlas*.

[27]Historical population density is taken from the History Database of the Global Environment (HYDE) version 3.1. This raster data on historical population can be downloaded from `ftp://ftp.mnp.nl/hyde/hyde31_final`. Documentation of the data is provided elsewhere (Bouwman et al., 2006; Klein Goldewijk, 2005; Klein Goldewijk et al., 2010).

Because we do not know the slave catchment areas for each port, we measure temperature shocks at ports rather than in the interior. As an alternative, we compute temperature shocks experienced by the ethnic groups surrounding each port. For each port, we identify the ethnic groups mapped by Murdock (1959) that have centroids within 500 km of of the port. For each of these groups, we use the temperature point closest to the group's centroid to compute annual temperatures. For these same groups, Nunn and Wantchekon (2011) report the number of slaves exported across the Atlantic over the course of the entire slave trade. We use these sums to weight the temperature shocks for the ethnic groups surrounding each port, thus constructing an "interior ethnic groups" shock for each port. As reported in the online appendix, these interior shocks have an effect with a magnitude close to our baseline. Results are similar if cutoffs of 250km or 1000km are used for assigning ethnic groups to ports (not reported).

We also validate the use of temperatures at coastal ports as a proxy for conditions in the interior by showing that temperature shocks in modern data are strongly correlated over space. We collect data on annual African temperatures from 1980-2000, reported on a $0.5°$ by $0.5°$ grid by the University of Delaware.[28] To make the estimation computationally feasible, we reduce the resolution of this data to a $3°$ by $3°$ grid. Creating every pairwise merge between ports in the data, we test whether temperatures at point j affect temperatures at point i by estimating:

$$temperature_{it} = \sum_{k=1}^{K} \beta_k D_{ij,k} \times temperature_{jt} + \delta_{ij} + \eta_t + \epsilon_{ijt} \tag{2}$$

Here $D_{ij,k}$ is a dummy variable for whether point i and j are within distance band k. We use 100 kilometer distance bands (200-300 km, 300-400 km, and so on). δ_{ij} is a fixed effect for each pair i, j. η_t is a year fixed effect, and ϵ_{ijt} is error. We show in the online appendix (Table A4) that shocks are remarkably persistent across space. For example, the β_k corresponding to a distance band of 500 km to 600 km suggests that a $1°C$ shock between 500 and 600 km away raises local temperature by slightly more than $0.5°C$. Temperatures measured at ports, then, are valid proxies for conditions in the interior.

3.3.3. *Level of observation.* Our results are not sensitive to the use of ports as the unit of observation. We collapse the African coastline into grid squares one degree in longitude by one degree in latitude. We take the sum of all slaves exported from within that grid square as slave exports, and the average temperature for ports within that square as the temperature for that square. The results are very similar to our baseline specification. Results are similar if they are collapsed into squares five degrees by five degrees. This is equivalent to collapsing to the nearest point in the climate data. Similarly, if we collapse slave exports into the major regions of the slave trade (Senegambia, Sierra

[28]These are available at `http://climate.geog.udel.edu/~climate/`.

Leone, the Windward Coast, the Gold Coast, the Bight of Benin, the Bight of Biafra, West-Central Africa, and Southeastern Africa), again using the average temperature across ports within a region to measure the aggregated temperature, we find a large negative impact of temperature on slave exports. Our main result holds if ports are collapsed by the ethnic groups into which they fall, as mapped by Murdock (1959). If we collapse the data into five-year averages, the results are again similar to the baseline.

3.3.4. *Outliers.* We discard statistical outliers, re-estimating the results using ordinary least squares (OLS), calculating dfbeta statistics, and then re-estimating the main tobit specification without observations whose absolute dfbeta is greater than $2/\sqrt{N}$.[29] Similarly, we show that we can achieve our main results without relying on certain subsets of the data. We eliminate the smaller ports in the sample by removing the bottom 50% of ports by total number of slaves exported. We also show that the results are not driven by inactive ports by excluding all observations from the data where a port has either ceased to export slaves, or has not yet begun its participation in the trade.

3.3.5. *Estimator.* We employ several alternative estimation strategies. We begin by re-estimating the main equation using OLS. The effect of a temperature shock remains negative and significant. Unsurprisingly, the estimated effect is smaller if we do not account for censoring. Using Conley (1999) standard errors and allowing spatial dependence over distances of up to 10 decimal degrees, the estimated standard error rises, but the result is still significant at the 5% level. We also find a significant and negative effect of temperature when discarding observations with no slave exports or including lagged temperature as a control.[30] Using a binary indicator for nonzero slave exports as the dependent variable, we again find a negative effect of temperature. Dividing this by quintiles of mean exports, we find a negative and significant response to temperature along the extensive margin for the lowest three quintiles, and a negative insignificant response at the top two (not reported). The coefficient estimate remains large and negative if the running maximum of slave exports added to the baseline as an additional control; the same is true when including ten-year running means of temperature or its variance (not reported).

The number of observations is large relative to the number of fixed effects, and so the incidental parameters problem should only be a minor concern. However, because (1) is non-linear, Wooldridge (2002, p. 542) suggests including port-specific mean temperatures $\overline{temperature}_i$ rather than port fixed effects. Under the assumption that the port fixed effects δ_i are linearly related to the port-specific means ($\delta_i = \psi + a_i + \lambda\overline{temperature_i}$),

[29]The standard test of discarding high-leverage observations is not reported. Since no observations have leverage greater than $2(df+1)/N$, these results are identical to the main specification.

[30]Including lagged temperature does not change the coefficient on the contemporaneous year's temperature. The impact of lagged temperature are smaller than the impact of the contemporaneous year's temperature, and are not statistically significant after two lags. Both lags are also negative, so we find no evidence that societies compensate for a low-export year by exporting more slaves the following year.

this will give consistent estimates of β. The results are congruent with our baseline specification. We find a negative but marginally insignificant ($p = 0.13$) effect of temperature if we replace the year fixed effects with a quadratic time trend in our baseline specification. We also find a negative and significant effect of temperature using a Poisson model ($\hat{\beta} = -1.096, s.e. = 0.178$).[31]

3.3.6. *Inclusion of lag slave exports.* We include lagged slave exports as a control. Since slave exports in the previous year are correlated with the error term, we use the difference between slaves exported two years ago and slaves exported three years ago as instruments for lagged slave exports. Although the coefficient estimate is smaller than in the baseline, the results again suggest a sizable reduction in slave exports during warmer years. Roughly 1,900 fewer slaves are exported per port in a year with a $1°\text{C}$ rise in temperature.

Wooldridge (2005) suggests that censored models with a lagged dependent variable such as ours can be estimated by including lagged slave exports, mean temperature, and initial slave exports in the estimation. This is consistent under the assumption that the port-level fixed effects δ_i can be decomposed into $\delta_i = \psi + a_i + \lambda_1 slaves_{i0} + \gamma \overline{temperature_i}$. This decomposition assumes a relationship between the initial number of slaves from when the trade first started and the port-fixed characteristics and reduces it to a regular tobit estimation. Here too, warmer temperatures predict a sizeable reduction in slave exports, about 1,300 slaves per port in a year with a $1°\text{C}$ temperature shock.

Re-estimating the same specification using the Arellano-Bond estimator (using two lags as an instrument), we find that the estimated coefficient on temperature is very similar to the estimate obtained using OLS. This is larger than the coefficient obtained by including the lagged dependent variable and estimating the effect using OLS. This suggests that, if there is any bias on the estimated coefficient on temperature when including the un-instrumented lag, it is towards zero, understating the effect of temperature on slave supply.

4. PERSISTENCE

While colder years improved agricultural productivity, they also increased slave exports. The density of modern night-time lights – a proxy for economic activity – can be used to identify which effect dominated over the long run.[32]

Following Michalopoulos and Papaioannou (2013) and Henderson et al. (2012), we use night-time lights as a proxy for modern development. These have the advantage of overcoming the lack of reliable sub-national data on economic activity in sub-Saharan Africa (Jerven, 2013). These data are taken from the Defense Meteorological Satellite Program's Operational Linescan System. Henderson et al. (2012) provide a particularly

[31] Convergence could not be achieved using a negative binomial model.

[32] These were originally downloaded from `http://www.ngdc.noaa.gov/dmsp/global_composites_v2.html`, and have since been moved to `http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html`.

detailed description of the data. These data are collected by capturing satellite images of the earth between 20:30 and 22:00 local time and averaging them over the course of the year. The raw data are at a 30 second resolution, so that each pixel is roughly one square kilometer. Luminosity for each pixel is reported as a six-bit integer ranging from 0 to 63. For each of our 134 ports, we calculate the average light density in 2009 for pixels within 500 km.

We then use OLS to estimate:

$$\ln(lightdensity_i) = \beta weightedanomaly_i + x_i'\gamma + \epsilon_i. \tag{3}$$

Here, $weightedanomaly_i$ is the weighted sum of the temperature anomalies over the slave trade as a whole, weighted by the number of slaves exported from all ports in a particular year. That is:

$$weightedanomaly_i = \sum_t \frac{slaves_t \times anomaly_{it}}{\sum_t slaves_t} \tag{4}$$

Alternatively, we report specifications that average the anomalies over selected periods. As in our main analysis, the anomaly is signed; positive values indicate years that are warmer than the 1902-1980 mean, while negative values indicate years that are colder than the 1902-1980 mean. If $\beta > 0$, it would indicate that the net effect of unusually warm weather experienced during the slave trade was beneficial for modern development. That is, over the long run, the beneficial effects of limiting slave exports outweighed the adverse effects of temporarily reduced agricultural output.

x_i is a vector of controls that includes a constant, absolute latitude, longitude, the number of raster light density points within 500km of the port, dummies for AEZs, distance from the nearest Atlantic or Indian Ocean port of slave demand, and average temperature over the period 1902-1980. Standard errors are clustered by the nearest climate point. We report our results in Table 5. Past temperature shocks predict higher incomes in the present, suggesting that, over the long-run, the effects of the reduction in slave exports out-weigh those of the losses to agriculture. In particular, it is temperature shocks during the late eighteenth century peak of the slave trade that best predict luminosity in the present.

These results echo those of Nunn (2008) at a local level; the slave trade hindered African development over the long run. Temperature is one of the many variables that affected participation in the slave trade. The literature has proposed multiple mechanisms for this, and we test several possibilities in Table 5. First, Fenske and Kala (2014) have shown a long-run effect of nineteenth-century slave exports on conflict in the present day. Drawing 500km circles around each of the ports in our data, we show that areas that experienced greater temperatures at the peak of the slave trade experience less violence in the present. We use two separate measures of violence: battles recorded for the period 1997 to 2013 in the Armed Conflict Location and Event data project,[33] and battle deaths for the period 1989 to 2010 recorded in the UCDP Georeferenced Event Dataset, version 1.5-2011.[34] Both measures of conflict are negatively correlated with $weightedanomaly_i$.

Nunn and Wantchekon (2011) suggest, alternatively, that African ethnic groups that exported more slaves are less trusting in the present. We use the same Afrobarometer data that they use to show that areas that experienced higher temperatures during the slave trade are more trusting today.[35] We average the answers of respondents within 500km of each port to question 83, "Generally speaking, would you say that most people can be trusted or that you must be very careful in dealing with people?" A value of 0 corresponds to the answer "you must be very careful," while a value of 1 corresponds to the response that "most people can be trusted." This measure of trust is positively correlated with $weightedanomaly_i$.

Obikili (2013b) and Whatley (2012) have argued that the slave trade increased the fragmentation and absolutism of traditional political authorities. We use the fourth round of the Afrobarometer to show that higher temperatures during the slave trade predict better traditional and local governments today.[36] We average the answers of respondents within 500km of each port to two questions. The first, 54c, asks respondents "How much of the time do you think the following try their best to listen to what people like you have to say: Traditional leaders." Answers range from 0 (never) to 3 (always). The second, 70c, asks respondents to rate the performance of their local government councilor on a scale from 1 (strongly disapprove) to 4 (strongly approve). Both measures of local government quality are positively correlated with $weightedanomaly_i$.

Finally, Dalton and Leung (2013) and Edlund and Ku (2014) have suggested that the slave trade changed the role of women in African society. We use the Demographic and Health Surveys to show that higher temperatures during the slave trade predict better outcomes for women today.[37] We average the answers of respondents within 500km of each port to two questions. The first, 511, asks respondents their age at first marriage.

[33] http://www.acleddata.com/data/

[34] http://www.pcr.uu.se/research/ucdp/datasets/ucdp_ged/

[35] Survey data are taken from http://www.afrobarometer.org/. Co-ordinates are available from http://scholar.harvard.edu/files/nunn/files/afrobarometer_r3_location_data.zip.

[36] Survey data are taken from http://www.afrobarometer.org/ To our knowledge, no co-ordinates exist for respondents. Rather, we use the ethnicity centroids reported by Deconinck and Verpoorten (2013) at http://qed.econ.queensu.ca/jae/2013-v28.1/deconinck-verpoorten/

[37] Data are available from http://dhsprogram.com/Data/. Our sample consists of the most recent Individual Recode standard DHS data for each country that have geographic coordinates. If no standard DHS data are available, we use the most recent Malaria Information Survey that has geographic coordinates. In particular, we use Angola 2011, Benin 2011-12, Burkina Faso 2010, Cameroon 2011, Central African Republic 1994-95, Congo Democratic Republic 2007, Cote d'Ivoire 2011-12, Ethiopia 2011, Ghana 2008, Guinea 2012, Kenya 2008-09, Lesotho 2009, Liberia 2007, Madagascar 2008-09, Malawi 2010, Mali 2006, Mozambique 2011, Namibia 2006-07, Niger 1998, Nigeria 2013, Rwanda 2010, Senegal 2010-11, Tanzania 2011-12, Togo 1998, Uganda 2011, Zambia 2007, and Zimbabwe 2010-11.

The second, v212, asks their age at first birth. Both measures of female empowerment are positively correlated with $weightedanomaly_i$.

In Table A6 in the online appendix, we report robustness checks. Results are similar if ports that do not export slaves over our time period are discarded, and if a control is added for whether the port is in the national capital. Our principal specification with controls remains significant at the 10% level when Conley (1999) standard errors are adjusted for spatial dependence over distances of ten decimal degrees. In Table A7, we report additional checks. First, we show that greater anomalies do not predict greater luminosity at points along the sub-Saharan coast that are not near slave ports.[38] The unconditional correlation is much smaller, and turns negative once additional controls are added. Second, we show that the result survives additional controls – distance from the national capital, distance from the nearest foreign border, petroleum, and malaria suitability.[39]

5. Interpretation

5.1. **Argument.** We argue that higher temperatures raised the cost of slave capture and export. Consider a coastal African ruler who maximizes profits from selling slaves, as in Fenoaltea (1999). The ruler "produces" a quantity S of slaves using an army that he controls. He may or may not be a price taker, and traders at the coast will pay $p(S)$ per slave. We assume the inverse demand function is downward-sloping: $p_s \leq 0$. The cost of raiding for S slaves is $C(S,T)$, where T is temperature. Costs are convex in both the quantity of slaves exported and in temperature. That is, $C_S > 0$, $C_{SS} > 0$, $C_T > 0$, and $C_{ST} > 0$. The ruler, then, will choose S to maximize $p(S)S - C(S,T)$. So long as demand is not "too convex,"[40] temperature reduces exports:

$$\frac{dS}{dT} = \frac{C_{ST}}{p_{ss}S + 2p_s - C_{SS}} < 0.$$

The critical assumption is that $C_{ST} > 0$. We believe this for four reasons. First, the ruler's costs of extracting tribute in order to feed a slave-harvesting army rise during bad harvests. This can be due to greater peasant resistance, or to greater prices of food in the interior. At Luanda, for example, prices of provisions were responsive to weather shocks (Miller, 1996, p. 397). Second, the mortality of slaves, soldiers and porters will rise in warmer years. In addition, with greater morbidity, the ruler's cost of providing slaves of

[38] These are taken from a set of 500 station points at equal intervals on the African coastline. This number gives them a spacing roughly equal to that of the slave ports.

[39] Distance from the national capital is computed using the sphdist function in Stata. Distance from the nearest foreign border is computed using ArcMap. Petroleum is an indicator for whether the port overlaps with an oilfield mapped in `http://www.prio.no/CSCW/Datasets/Geographical-and-Resource/Petroleum-Dataset/Petroleum-Dataset-v11/`. Malaria suitability is the average within 500km, as mapped by `www.map.ox.ac.uk`.

[40] That is, $p_{ss}S + 2p_s - C_{SS} < 0$.

any given quality will rise. Third, higher temperatures lead to greater evapotranspiration, increasing the probability that drought will set in. Areas of slave supply become more disordered, raising the costs of raiding directly. Finally, the slave trade depended on complementary economic activities that provisioned ships, fed the populations of the ports, and supplemented the incomes of slave traders.

There are a priori mechanisms that predict a higher slave supply in worse agricultural years, such as people selling themselves or family members into slavery to avoid starvation. However, our findings strongly suggest that the net impact of slave exports in years of higher temperature was negative. While we discuss these opposing mechanisms briefly, we focus on the mechanisms that contribute to the negative impacts on slave exports that we find dominate in the results.

5.2. **Temperature, agriculture, and mortality.** There is substantial evidence that temperature shocks affect agriculture and mortality in the present. Studies of the impact of climate on modern agricultural productivity in Africa (Kala et al., 2012; Kurukulasuriya and Mendelsohn, 2008) indicate that higher temperatures relative to the baseline climate have a negative impact on productivity, particularly for non-irrigated agriculture. In addition, higher temperatures increase evapotranspiration (Brinkman and Sombroek, 1996). This indicates that colder years lead to a relatively higher level of water availability for plants, which is crucial in certain stages of plant growth. Similarly, organic matter in the soil decomposes faster in higher temperatures (Bot and Benites, 2005). Other studies of temperature impacts on the productivity of tropical agriculture find similar results (Guiteras, 2009; Sanghi and Mendelsohn, 2008) Thus, the link between colder years and higher agricultural productivity in the tropics is well established.

There is also evidence that higher temperatures increase disease burdens that raise mortality (Burgess et al., 2011). Studies of the relationship between disease and temperature find that higher temperatures are more conducive to the spread and transmission of diseases such as malaria and yellow fever (Alsop, 2007). Malaria and yellow fever have placed a particularly heavy mortality burden on Africa throughout the continent's history (Gallup and Sachs, 2001; Ngalamulume, 2004). Further, arid AEZs and modern-day child malnutrition are positively correlated (Sharma et al., 1996).

5.3. **Case studies.** The histories of Benguela, Whydah, and Mozambique are consistent with our interpretation of our empirical findings. These three cases are statistically influential, well documented, and come from three separate regions. For each, we describe the effects of adverse weather and outline the interdependence between the slave trade and the broader economy.

5.3.1. *Benguela.* Between 1695 and 1850, Benguela sent nearly half a million slaves to the new world (Candido, 2006, p. 18). In West-Central Africa, adverse climate events reduced slave exports through three main channels. First, the resources available for slave capture were greater in good years. Military forces timed their expeditions to take advantage of the seasonal availability of ripening fields and full granaries for plunder (Miller, 1996, p. 48, 147). Portuguese soldiers in the interior were often without a regular salary, and so exchanged gunpowder inland for chickens and other agricultural products (Candido, 2006, p. 38). Military officials bought food and other commodities using trade goods such as beads and textiles (Candido, 2006, p. 112). Slaves were marched to the coast by caravan, and caravan porters used these as opportunities to trade on their own accounts (Candido, 2006, p. 124).

Second, periods of higher temperatures, in addition to providing fewer trade opportunities, would have been times of greater mortality for both slaves and porters. The mortality of slaves between capture and the coast may have been over 50% in eighteenth-century Angola (Miller, 1996, p. 120). After one long drought period, many slaves in Luanda were sick and dying (Miller, 1996, p. 178).

Third, droughts produced "violence, demographic dispersal, and emigration" (Miller, 1982, p. 32). Confrontation between Portuguese forces and African states occurred with "suspicious regularity at the end of periods of significantly reduced precipitation" (Miller, 1982, p. 24). Tribute from local Sobas was often rendered in the form of slaves (Candido, 2006, p. 24), and so disruption to the political order constricted the flow of slaves. Famines pushed Africans to resettle in more distant regions (Candido, 2006, p. 48), raising the costs of capture. The movement of villages in response to drought was so frequent in South-Central Africa that permanent dwellings were rarely built (Miller, 1996, p. 157).

5.3.2. *Whydah.* Whydah was Dahomey's principal port. Congruent with our model, the principal sources of slaves after 1730 were capture by the Dahomean army and purchase from the interior (Law, 2004, p. 138). The success of the slave trade, then, responded to the resources available to the state. Dahomey competed with other states of the "Slave Coast" to supply slaves for the Atlantic trade (Law, 2004, p. 126). Conflict was seasonal, as wetter periods increased the threat that tsetse flies posed to Oyo's cavalry (Law, 1975). Middlemen supplemented the royal trade by purchasing slaves from neighboring areas (Law, 2004, p. 111). Their ability to acquire slaves was tied to conditions in regions of slave supply; in the 1770s and 1780s, for example, disturbances on the coast made it difficult to buy slaves in eastern markets (Ross, 1987, p. 370). Middleman trade also depended on the strength of the Dahomean army. It was the Dahomean conquest of alternative ports such as Jaquin and Apa that drove trade towards Whydah (Ross, 1987, p. 361).

The slave trade was supported by local retail, agriculture, fishing and salt-making (Law, 2004, p. 77). The city depended on goods imported from the interior that were consumed locally, including kola from Asante and natron from Borno (Law, 2004, p. 83). The trade itself depended on the labor of local porters, water-rollers, laundry women, and other workers (Law, 2004, p. 147). Adverse shocks to these other sectors, including weather shocks, raised the costs of provisioning the slave trade.

5.3.3. *Mozambique.* Slave exports from Mozambique Island accelerated from the 1770s and grew until the 1830s (Newitt, 1995, p. 245-6). Severe "*mahlatule*" droughts occurred from 1794 to 1802 and from 1823 to the late 1830s. Local people intensified activities such as hunting, gold mining and trading. When these failed, they turned to out-migration, which led to instability, war, banditry and slaving (Newitt, 1995, p. 253). The long second drought upended peasant life, and much of the population starved, died of smallpox or moved elsewhere (Newitt, 1995, p. 254). This made slave capture more costly.

By disrupting settlement patterns, trading networks, and local states, droughts raised the costs of slaving. The Nguni states that were pushed north of the Zambezi by the *mahlatule* were known for their fierceness and economic self-sufficiency, which isolated the region from trade (Newitt, 1995, p. 264). Droughts slowed Portuguese movement into the interior and made rivers transport difficult (Newitt, 1995, p. 255, 264, 284).

The island depended on food from the mainland (Newitt, 1995, p. 190). Slave ships were similarly dependent on local food and supplies (Newitt, 1995, p. 249). These needs were keenly felt in periods of bad weather; the island was forced, for example, to import food during the drought in 1831 (Alpers, 2001, p. 77).

6. Conclusion

We find that environmental shocks within Africa influenced the dynamics of the slave trade. The effects we find are large. A temperature increase of one degree Celsius reduced annual exports by roughly 3,000 slaves per port. We interpret these as shifts in the cost of slave supply, operating through mortality and the productivity of complementary sectors. The histories of Benguela, Whydah, and Mozambique support our interpretation. Past temperature shocks predict economic activity today.

We have advanced the existing understanding of Africa's participation in the slave trade by incorporating previously unutilized, time-varying measures of weather shocks spanning all sending regions. This exercise demonstrates the importance of supply-side factors in the dynamics of the transatlantic slave trade. This has also enabled us to provide new evidence on the channels through which geography shapes economic development in a historical setting. We are able to examine the responsiveness of a different form of conflict to economic shocks than is typically studied in the literature. Rather than being encouraged by economic distress, slave raiding was hindered by it.

There are, of course, limitations to our approach. Data availability prevent us from looking at the dynamics of the Indian Ocean, Red Sea, or internal African slave trades. Similarly, we are unable to examine the period before 1730, or environmental factors other than temperature. Further, our results should not be over-extrapolated. Depending on their resource endowments and institutions, societies may adapt to change, particularly to slow-moving changes in climate. As climate scientists advance in their reconstruction of the environmental past, we are hopeful that it will become possible to examine these issues further and to better understand the long-run causes of development.

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Table 1: Summary statistics

	(1) Mean	(2) s.d.	(3) Min	(4) Max	(5) N
Slaves exported	444	1,813	0	34,927	18,358
Slaves (non-zero)	2,543	3,673	1.23	34,927	3,206
Temperature (interpolated)	25.2	2.33	13.3	27.5	18,358
Temperature (closest point)	25.2	2.34	13.3	27.4	18,358
Climate (30 year mean temperature)	25.2	2.32	13.4	27.3	18,224
Deviation from 30 year mean temperature	-0.00043	0.13	-0.86	0.62	18,224
Year	1,798	39.5	1,730	1,866	18,358
AEZ: Desert	0.030	0.17	0	1	18,358
AEZ: Subhumid	0.28	0.45	0	1	18,358
AEZ: Forest	0.43	0.50	0	1	18,358
AEZ: Dry Savannah	0.15	0.36	0	1	18,358
AEZ: Moist Savannah	0.11	0.32	0	1	18,358

Table 2: Main results

	(1)
Temperature	-3,052.058***
	(1,114.903)
Year F.E.	Y
Port F.E.	Y
Observations	18,358
Clusters	28

Notes : ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by closest climate point in parentheses. The dependent variable is slave exports. All regressions are tobit. † Anomaly used in place of temperature.

Table 3: Results by region

	(1)	(2)		(3)	(4)	(5)
Temperature X			Temperature (interpolated)		-3,148.175***	
Desert	-3,862.564***				(980.134)	
	(1,287.854)		Temperature X			
Dry Savannah	-3,924.755***		Humidity above median		3,233.835***	
	(937.347)				(962.822)	
Sub-Humid	-2,643.042*		Senegambia			-1,475.200**
	(1,367.530)					(642.892)
Moist Savannah	-1,570.850*		Sierra Leone			389.839
	(824.036)					(996.694)
Humid Forest	239.182		Windward			2,322.019
	(1,289.700)					(1,633.087)
Cereals		-3,472.447***	Gold Coast			-982.343
		(1,182.922)				(1,228.014)
Roots		-2,715.040	Benin			-2,856.152*
		(1,963.234)				(1,692.232)
Trees		1,893.372*	Biafra			379.252
		(1,099.699)				(1,404.252)
None		676.444	West-Central			-3,792.429***
		(1,373.256)				(895.225)
			Southeast			-5,565.669**
						(2,181.252)
Year F.E.	Y	Y			Y	Y
Port F.E.	Y	Y			Y	Y
Obs.	18,358	18,358			18,358	18,358
Clusters	28	28			28	28

Distribution of crop types by AEZ

	Cereals	None	Roots and Tubers	Tree Fruits
Desert	25.00	0.00	50.00	25.00
Dry Savannah	95.00	5.00	0.00	0.00
Sub-Humid	41.38	3.45	55.17	0.00
Moist Savannah	93.33	0.00	6.67	0.00
Humid Forest	37.84	0.00	48.65	13.51
Total	53.73	2.24	39.55	4.48

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by closest climate point in parentheses. The dependent variable is slave exports. All regressions are tobit. † Anomaly used in place of temperature.

Table 4: Climate

	(1)	(2)	(3)
	Climate computed as 30 year moving average		
Deviation from temperature normal	-1,244.187**		-2,640.058***
	(529.643)		(877.715)
Temperature normal		-18,584.020***	-20,727.839***
		(6,904.375)	(7,297.426)
Obs.	18,224	18,224	18,224
Clusters	28	28	28
	Climate computed using bandpass filter		
BK Filter Temperature Shock	-854.416		11.203
	(560.692)		(497.584)
BK Filter Temperature Trend		-7,222.670***	-7,224.724***
		(2,279.920)	(2,280.156)
Obs.	17,554	17,554	17,554
Clusters	28	28	28
Year F.E.	Y	Y	Y
Port F.E.	Y	Y	Y

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by closest climate point in parentheses. The dependent variable is slave exports. All regressions are tobit. † Anomaly used in place of temperature.

Table 5. The modern impact of past temperature anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Dependent variable is log light density							
Anomaly	0.794*	0.721**	0.065*	0.050*	0.139*	0.059	0.166**	0.050*
	(0.462)	(0.337)	(0.034)	(0.029)	(0.071)	(0.040)	(0.066)	(0.026)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	Weighted	Weighted	1730s	1740s	1750s	1760s	1770s	1780s
Obs.	120	120	134	134	134	134	134	134
Clusters	26	26	28	28	28	28	28	28
R2	0.137	0.495	0.482	0.478	0.484	0.464	0.500	0.480
Anomaly	0.037	0.050	0.019	0.036	0.044	0.031	0.035	0.047
	(0.025)	(0.033)	(0.033)	(0.042)	(0.036)	(0.026)	(0.028)	(0.039)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	1790s	1800s	1810s	1820s	1830s	1840s	1850s	1860s
Obs.	134	134	134	134	134	134	134	134
Clusters	28	28	28	28	28	28	28	28
R2	0.465	0.474	0.444	0.449	0.458	0.456	0.461	0.459
	Panel B. Other Modern Outcomes							
	Battles	*Battle Deaths*	*Trust*	*Traditional Authorities Listen*	*Performance of Local Council*	*Age at first marriage*	*Age at first birth*	
Anomaly	-2,957.755***	-21.192**	0.183**	1.011***	0.453**	1.868***	4.471***	
	(484.963)	(7.575)	(0.080)	(0.125)	(0.175)	(0.590)	(0.580)	
Controls	Y	Y	Y	Y	Y	Y	Y	
Time Period	Weighted	Weighted	Weighted	Weighted	Weighted	Weighted	Weighted	
Obs.	120	115	80	103	103	111	115	
Clusters	26	23	21	21	21	22	23	
R2	0.650	0.304	0.669	0.596	0.790	0.856	0.879	

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by closest climate point in parentheses. All regressions are OLS. The dependent variable is log light density. All regressions include a constant. Controls are absolute latitude, longitude, the number of raster light density points within 500km of the port, dummies for AEZs, distance from the nearest Atlantic or Indian Ocean port of slave demand, and average temperature over the period 1902-1980.

Online appendix: Not for publication.

APPENDIX A. MISSING DATA

We use the ship-level data to describe the variables that predict data quality in Table A5. We use whether the principal port of slave purchase is missing as an indicator of data quality. Without adding additional controls, it is clear that the data improve in quality from 1500 to 1550, before declining steadily to 1750. Data begin to improve again after 1750, only to become worse after the suppression of the slave trade in the early 1800s. However, these trends are confounded by the changing composition of the slave trade over time, across national carriers, and regions of slave purchase. Relative to British ships, French and Portuguese carriers are less likely to lack data on the port of principal slave purchase. Controlling for time, however, reveals the Portuguese data to be of a lower quality. Relative to Southeast Africa, data from other regions, excepting the Gold Coast, tend to be of worse quality.

In addition, there are 20,143 voyages occurring after 1729 for which the major region of slave purchase is known. We merge these to the annual temperatures of the regions in our data, averaged over ports within each region. We regress whether the port of slave purchase is missing on temperature, region fixed effects, and year fixed effects. We find that a one degree temperature increase predicts a 2.60 percentage point reduction in the probability that the port of slave purchase is missing. The heteroskedasticity-robust standard error of this estimate is 3.05 percentage points, making it insignificant at conventional levels.

APPENDIX B. IMPACTS OF TEMPERATURE ON WIND SPEED

We use data from on modern temperature and wind speed from the NCC (NCEP Corrected by CRU) model, housed at the Laboratoire de Météorologie Dynamique (Ngo-Duc et al., 2005). This is a global model at the 1° by 1° level, with observations available at 6-hourly intervals from 1948-2000 (We use the years 1950-2000). Ngo-Duc et al. prepare these data using satellite data as inputs into a global circulation model, correcting them using station-level data from the Climate Research Unit at East Anglia. Our regression specification is:

$$wind_{it} = \alpha + \beta temperature_{it} + point_i + year_t + \epsilon_{it},$$

where $wind_{it}$ and $temperature_{it}$ is the mean annual wind speed in m/s and mean annual temperature in degrees Celsius at point i in year t, respectively, $point_i$ is the point fixed effect, and $year_t$ is the year fixed effect. We run this specification both at the global level, and for the region around Africa (which restricts latitude to between -50 and 50 and longitude to between -40 and 60).

APPENDIX C. DETAILED DESCRIPTION OF THE TEMPERATURE DATA

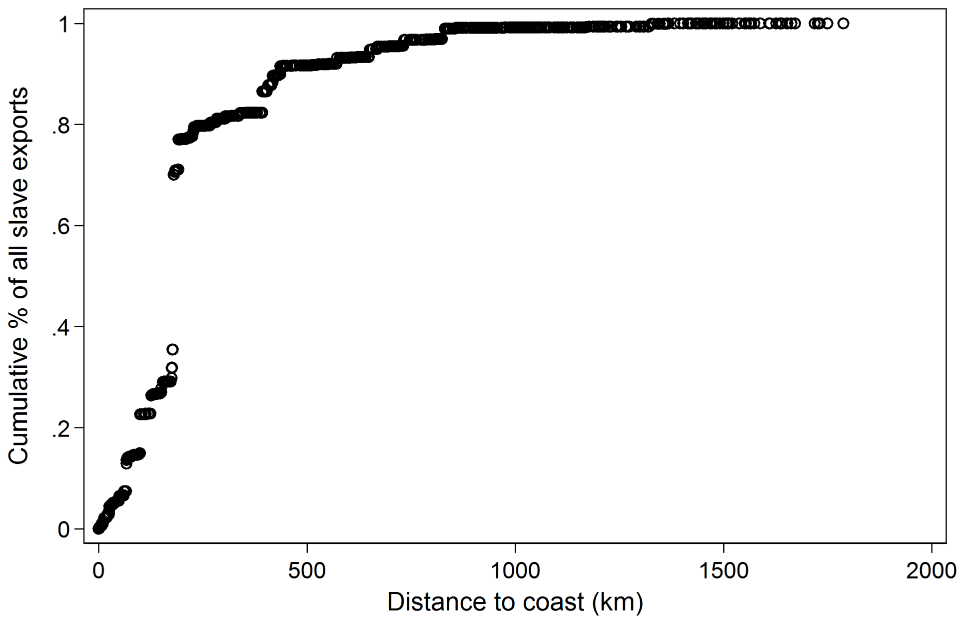
We use the temperature data constructed by Mann et al. (1998a,b), a multi-proxy gridded series of annual temperature shocks (relative to 1902-1980) reconstructed from the year 1400 onwards. The authors use previously available long instrumental records of a variety of proxy indicators, such as dendroclimatic records, ice cores, and ice melt records, and combine them in a single multi-proxy series of temperature records. This construction of a single time-series for each 5° by 5° point takes into account the unique uncertainties and reconstruction issues for each proxy indicator, and the presence of multiple and independent sources of proxy data implies that their estimates are relatively robust to the limitations of using a single source of paleoclimatic data. Furthermore, they use available instrumental temperature records from the early twentieth century, 1902-1995 in particular, to calibrate the historical estimates of temperature.

The variability in the modern instrumental temperature measurements is decomposed into eigenvectors, each of which has an associated empirical orthogonal function (EOF) which describes its spatial variability as well its principal component (PC) that describes its temporal evolution. The first five of these eigenvectors explain 93% of the variation in global mean temperatures. Then, each of the historic proxy records are calibrated using these eigenvectors separately, and the reconstructed multi-proxy temperature series is obtained using optimization methods to determine the optimal combination of eigenvectors represented by the multi-proxy data.

An advantage of using this approach is that known phenomena affecting long-range patterns of variability such as the El Ninõ/Southern Oscillation (ENSO) can be exploited to reconstruct temperature in areas for which paleoclimatic records are not directly available. This is done by using the known form of these teleconnections and the presence of paleoclimatic records in locations that are linked through these patterns. The results obtained were verified using numerous robustness checks, including examining region-level data with the availability of very long instrumental records, as well as the ability of the series to reproduce known historical events such as the 1791 strong El-Ninõ year and the 1815 Tambora volcano eruption that caused lower temperatures in 1816.

APPENDIX D. SLAVE EXPORTS AND COAST DISTANCE

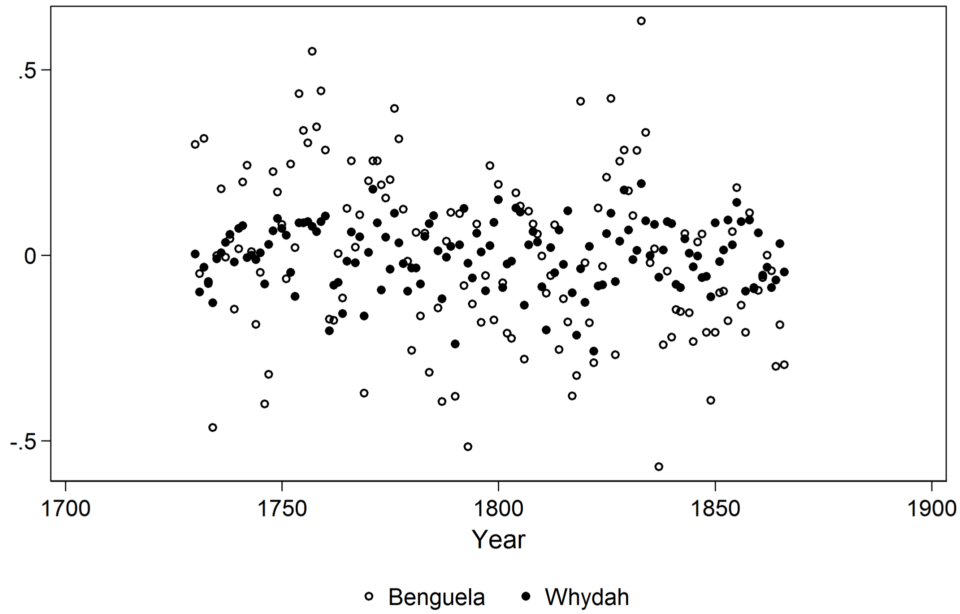
FIGURE A.1. Slave exports and distance from coast



Notes: This figure plots the cumulate percentage of all exports in the Indian Ocean and Atlantic slave trades, reported in Nunn and Wantchekon (2011), against the distance of each ethnic group centroid from the coast.

APPENDIX E. DATA EXAMPLE

FIGURE A.2. Temperature deviations from mean: Benguela and Whydah



Notes: Temperature deviations from port means are in degrees celsius.

APPENDIX F. KERNEL DENSITIES

FIGURE A.3. Kernel densities of slave exports

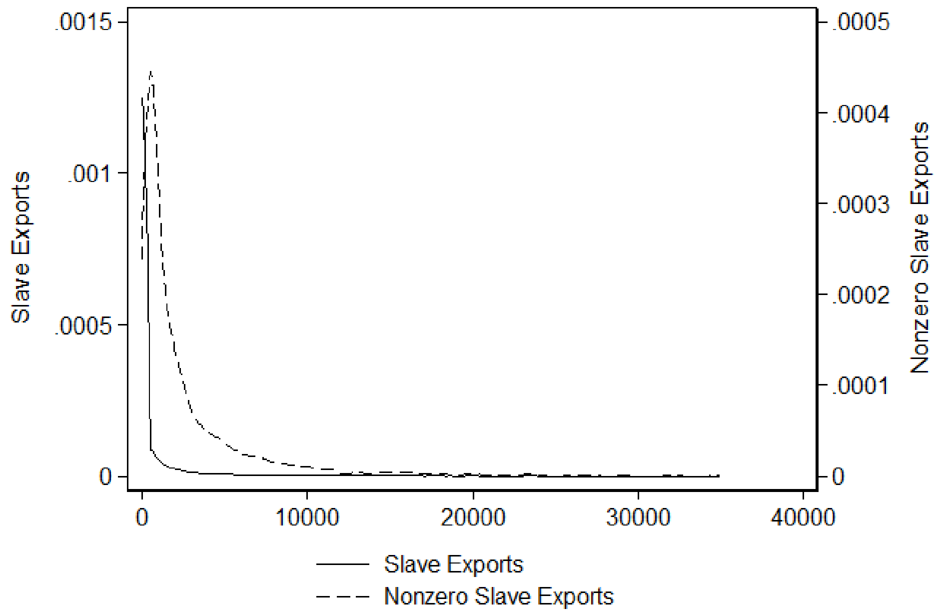


FIGURE A.4. Kernel density of time to departure from Africa

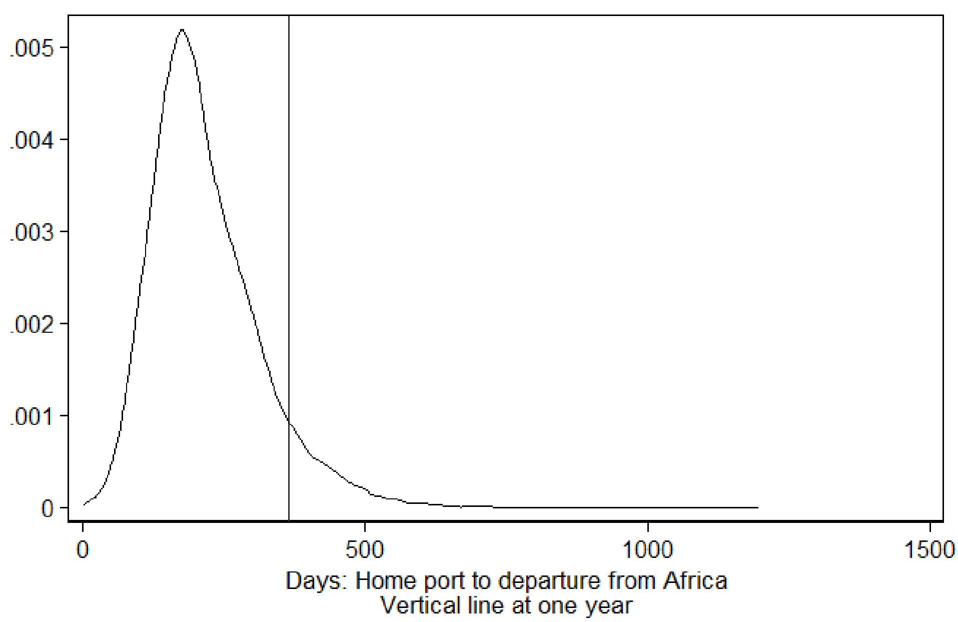


Table A0. Alternative standard errors using a linear estimator

	(1)
Anomaly (Interpolated)	-576.496***
Standard errors clustered by	
Point X Year	(171.082)
1° by 1° square (72 squares)	(248.310)
2° by 2° square (50 squares)	(243.408)
3° by 3° square (38 squares)	(249.116)
4° by 4° square (29 squares)	(274.209)
5° by 5° square (24 squares)	(248.485)
Closest temperature point (28 points)	(249.538)
CGM standard errors clustered by	
Point X Year	(171.082)
1° by 1° square (72 squares)	(249.221)
2° by 2° square (50 squares)	(244.301)
3° by 3° square (38 squares)	(250.031)
4° by 4° square (29 squares)	(275.215)
5° by 5° square (24 squares)	(249.397)
Closest temperature point (28 points)	(250.454)
Closest temperature point and year	(286.322)
Observations	
Year FE	Y
Port FE	Y

The dependent variable is slave exports. All regressions are OLS with port and year fixed effects unless otherwise indicated.

Table A1: Robustness checks 1

Heterogeneity					
Linear port trends	-1,679.160**	*Including Temperature X Tsetse Suitability*	-4,420.368***	*Known slaves + Region known*	-2,132.065***
	(669.884)		(1,631.667)		(772.722)
Obs.	18,358	*Coef. on Temp X Tsetse*	1,750.484	Obs.	18,358
			(1,986.938)		
Quadratic region trends †	-1,704.421***	Obs.	17,536	*Slaves landed in New World*	-2,647.996***
	(624.310)				(999.666)
Obs.	18,358	*Dropping US Civil War*	-3,032.921***	Obs.	18,358
			(1,107.456)		
Pre-1807	-2,145.928**	Obs.	17,688	*Closest temperature point*	-2,629.395***
	(929.265)				(790.065)
Obs.	10,318	*Including interaction with El Nino Years*	-3,016.934***	Obs.	18,358
			(1,097.403)		
Post-1806	-2,191.968*	*Coef. on Temp X El Nino*	-27.898	*Temperature: Ethnicities within 500 km*	-2,485.806***
	(1,242.838)		(47.893)		(898.906)
Obs.	8,040	Obs.	18,358	Obs.	17,380
Active ports only	-2,307.081***	*Control for climate trend at NW port*	-2,635.310***	*Slaves normalized by population density*	-760.331***
	(776.294)		(921.508)		(271.219)
Obs.	6,780	Obs.	17,408	Obs.	18,358
Control for New World Temperature	-3,090.331***	*Including neighbor's anomaly †*	-10,441.490*	*No temperature points over water*	-3,005.996***
	(1,116.947)		(5,792.334)		(629.668)
Obs.	18,358	*Coef. on neighbor's anomaly*	7,475.588	Obs.	18,358
			(5,298.468)		
Control for prices	-2,235.841**	Obs.	18,358	*Log temperature on RHS*	-76,199.646***
	(882.578)				(25,762.309)
Obs.	10,854	*Control for slave trading power's shock*	-3,084.699***	Obs.	18,358
			(1,141.105)		
Temperature shock at modal destination	-3,315.021***	Obs.	18,358	*Log (1+slave exports) on LHS*	-95.373***
	(1,141.054)				(27.881)
Obs.	17,536	*De-meaned temperature if ≥ 0*	-3,270.425**	Obs.	18,358
			(1,297.770)	Outliers	
Including Temperature X Bovines	-4,189.436***	*De-meaned temperature if < 0*	-2,871.418**	*No high dfbeta*	-2,019.513***
	(1,054.179)		(1,268.771)		(612.161)
Coef. on Temp X Bovines	2,644.148**	Obs.	18,358	Obs.	17,816
	(1,234.415)				
Obs.	18,358	Measurement		*Top 50% of ports*	-3,288.917***
		Known slaves	-1,848.221***		(1,153.896)
Including Temperature X Husbandry	-3,713.268*		(696.018)	Obs.	9,179
	(1,900.544)	Obs.	18,358		
Coef. on Temp X Husbandry	394.664			*Top 50% of years by port*	-1,885.934*
	(796.812)				(997.536)
Obs.	18,358			Obs.	9,246

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by closest climate point in parentheses. The dependent variable is slave exports. All regressions are tobit with port and year fixed effects unless otherwise indicated. † Anomaly used in place of temperature.

Table A2: Robustness checks 2

Level of observation		*Port mean anomaly*	-2,397.368**
Artificial squares (1x1)	-3,490.732**		(1,028.790)
	(1,395.269)	Obs.	18,358
Obs.	9,864		
Artificial squares (5x5)	-5,524.108***	*Include lag temperature*	-2,297.655***
	(2,098.764)		(790.881)
Obs.	3,836	Obs.	18,224
Region-level	-11,394.596*	*Quadratic in year, rather than FE*	-1,206.751
	(6,355.888)		(795.406)
Obs.	1,096	Obs.	18,358
Murdock ethnicities	-3,997.547***	*Including lag slave exports*	
	(1,339.742)	*Include lag slaves*	-1,858.215***
Obs.	7,672		(713.707)
Estimation		Obs.	18,224
OLS	-576.496**	*Instrument for lag slaves with lag difference*	-1,933.028***
s.e. clustered by point	(250.453)		(726.435)
s.e. clustered by Conley's method	(279.406)	Obs.	18,090
Obs.	18,358		
		Port mean anomaly, year F.E., lag slave	-1,340.205**
Dependent variable: Any slaves (OLS)	-0.064*		(603.091)
	(0.034)	Obs.	18,224
Obs.	18,358		
		OLS with lag	-387.113**
No zeroes (OLS)	-2,582.865**		(176.219)
	(953.700)	Obs.	18,224
Obs.	3,206		
		Arellano-Bond ‡	-613.994*
Collapse to 5-year intervals	-4,634.630***		(345.046)
	(1,759.778)	Obs.	18,090
Obs.	3,752		

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by closest climate point in parentheses. The dependent variable is slave exports. All regressions are tobit with port and year fixed effects unless otherwise indicated. † Anomaly used in place of temperature. ‡ Robust, rather than clustered, standard errors reported.

Table A3: Tests of coefficient equality in Table 3

	(1)	(2)	(3)	(4)
	p-values: Results by agro-ecological zone			
	Desert	Dry Savannah	Sub-humid	Moist Savannah
Dry Savannah	0.94			
Sub-humid	0.14	0.30		
Moist Savannah	0.02	0.00	0.35	
Humid forest	0.00	0.00	0.02	0.04
	p-values: Results by region			
	Senegambia	Sierra Leone	Windward	Gold Coast
Sierra Leone	0.03			
Windward	0.01	0.09		
Gold Coast	0.59	0.14	0.04	
Benin	0.28	0.02	0.01	0.06
Biafra	0.09	0.99	0.24	0.05
West-Central	0.01	0.00	0.00	0.00
Southeast	0.05	0.01	0.00	0.02
	Benin	Biafra	West-Central	
Biafra	0.02			
West-Central	0.49	0.00		
Southeast	0.19	0.00	0.40	

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. These p-values test the equality of the coefficients reported in Table 3 in the text.

Table A4: Temperature correlations over space: 1980-2000

	(1)
Temperature at point *j* X point is within:	
200 km to 300 km	0.654***
	(0.011)
300 km to 400 km	0.553***
	(0.004)
400 km to 500 km	0.486***
	(0.005)
500 km to 600 km	0.513***
	(0.015)
600 km to 700 km	0.384***
	(0.005)
700 km to 800 km	0.334***
	(0.004)
800 km to 900 km	0.388***
	(0.010)
900 km to 1000 km	0.285***
	(0.005)
1000 km to 1100 km	0.201***
	(0.005)
1100 km to 1200 km	0.213***
	(0.004)
1200 km to 1300 km	0.201***
	(0.007)
1300 km to 1400 km	0.122***
	(0.003)
1400 km to 1500 km	0.095***
	(0.004)
1500 km to 1600 km	0.170***
	(0.007)
1600 km to 1700 km	0.056***
	(0.003)
1700 km to 1800 km	0.048***
	(0.005)
1800 km to 1900 km	0.073***
	(0.005)
1900 km to 2000 km	0.055***
	(0.004)
Pair *(i,j)* FE	Y
Year FE	Y
Observations	2,332,440

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors in parentheses. The dependent variable is temperature. The estimator is OLS.

Table A5: Predictors of missing data

	(1)	(2)	(3)	(4)
(Year-1500) X (1500 to 1550)	-0.008***			-0.005***
	(0.000)			(0.000)
(Year-1550) X (1550 to 1600)	0.002***			-0.003***
	(0.001)			(0.000)
(Year-1600) X (1600 to 1650)	0.000			0.001***
	(0.001)			(0.001)
(Year-1650) X (1650 to 1700)	0.003***			0.002***
	(0.000)			(0.000)
(Year-1700) X (1700 to 1750)	0.003***			-0.000
	(0.000)			(0.000)
(Year-1750) X (1750 to 1800)	-0.003***			-0.002***
	(0.000)			(0.000)
(Year-1800) X (1800 to 1850)	0.003***			-0.003***
	(0.000)			(0.000)
(Year-1850) X (1850 to 1900)	0.039***			-0.015***
	(0.002)			(0.001)
Registered: France		-0.125***		-0.062***
		(0.008)		(0.005)
Registered: Portugal		-0.081***		0.059***
		(0.008)		(0.007)
Registered: Other		0.152***		0.146***
		(0.006)		(0.005)
Region: Senegambia			-0.115***	-0.148***
			(0.015)	(0.016)
Region: Windward			-0.155***	-0.163***
			(0.016)	(0.016)
Region: Sierra Leone			-0.158***	-0.205***
			(0.015)	(0.015)
Region: Gold Coast			0.112***	0.054***
			(0.015)	(0.016)
Region: Bight of Benin			-0.067***	-0.072***
			(0.015)	(0.015)
Region: Bight of Biafra			-0.033**	-0.089***
			(0.014)	(0.015)
Region: West-Central Africa			-0.107***	-0.162***
			(0.017)	(0.018)
Region: Missing			0.775***	0.733***
			(0.014)	(0.014)
Region: Other			0.368***	0.309***
			(0.019)	(0.020)
Observations	34,948	34,948	34,948	34,948

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Robust standard errors in parentheses. The dependent variable is a dummy for whether the major port of slave purchase is missing. All regressions are OLS.

Table A6. Robustness checks for modern outcomes

	Panel A: Discard inactive ports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomaly	0.794*	0.721**	0.044**	0.051	-0.066	0.044*	0.134**	0.048
	(0.462)	(0.337)	(0.018)	(0.045)	(0.045)	(0.021)	(0.050)	(0.034)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	Weighted	Weighted	1730s	1740s	1750s	1760s	1770s	1780s
Obs.	120	120	43	47	60	60	61	59
R2	0.137	0.495	0.749	0.558	0.597	0.610	0.541	0.792
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	
Anomaly	0.040	-0.007	0.031	0.023	0.070***	0.019	0.046***	
	(0.032)	(0.023)	(0.018)	(0.021)	(0.020)	(0.031)	(0.014)	
Controls	N	Y	Y	Y	Y	Y	Y	
Time Period	1790s	1800s	1810s	1820s	1830s	1840s	1850s	
Obs.	60	56	52	56	46	37	26	
R2	0.638	0.462	0.477	0.465	0.554	0.458	0.884	
	Panel B: Include "capital city" dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomaly	0.790*	0.726**	0.070*	0.053*	0.155**	0.062	0.178**	0.054*
	(0.453)	(0.345)	(0.035)	(0.030)	(0.069)	(0.042)	(0.068)	(0.027)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	Weighted	Weighted	1730s	1740s	1750s	1760s	1770s	1780s
Obs.	120	120	134	134	134	134	134	134
R2	0.137	0.495	0.490	0.485	0.494	0.470	0.509	0.488
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Anomaly	0.039	0.053	0.021	0.039	0.047	0.033	0.037	0.050
	(0.027)	(0.034)	(0.034)	(0.044)	(0.038)	(0.027)	(0.029)	(0.041)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	1790s	1800s	1810s	1820s	1830s	1840s	1850s	1860s
Obs.	134	134	134	134	134	134	134	134
R2	0.470	0.479	0.448	0.453	0.463	0.461	0.466	0.463

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors in parentheses clustered by closest climate point. All regressions are OLS. The dependent variable is log light density. All regressions include a constant. Controls are absolute latitude, longitude, the number of raster light density points within 500km of the port, dummies for AEZs, distance from the nearest Atlantic or Indian Ocean port of slave demand, and average temperature over the period 1902-1980.

Table A7. Additional robustness checks for modern outcomes

	Panel A: Points not within 500 km of ports							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomaly	0.000***	-0.000*	-0.059**	-0.039*	-0.070**	-0.040	-0.072*	-0.057**
	(0.000)	(0.000)	(0.026)	(0.020)	(0.030)	(0.026)	(0.035)	(0.027)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	Total	Total	1730s	1740s	1750s	1760s	1770s	1780s
Obs.	112	112	93	93	93	93	93	93
R2	0.233	0.830	0.864	0.852	0.867	0.833	0.836	0.851
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Anomaly	-0.018	-0.001	-0.018	-0.030*	-0.030	-0.028*	-0.019	-0.017
	(0.011)	(0.010)	(0.011)	(0.017)	(0.019)	(0.016)	(0.012)	(0.011)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	1790s	1800s	1810s	1820s	1830s	1840s	1850s	1860s
Obs.	93	93	93	93	93	93	93	93
R2	0.245	0.836	0.864	0.852	0.867	0.833	0.836	0.851
	Panel B: Additional controls							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomaly	0.794*	0.908***	0.079**	0.060*	0.227***	0.078*	0.184**	0.062**
	(0.462)	(0.304)	(0.038)	(0.032)	(0.081)	(0.045)	(0.076)	(0.030)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	All	All	1730s	1740s	1750s	1760s	1770s	1780s
Obs.	120	120	134	134	134	134	134	134
R2	0.137	0.703	0.630	0.623	0.651	0.619	0.644	0.632
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Anomaly	0.046	0.061	0.040	0.071	0.070	0.047	0.048	0.065
	(0.029)	(0.037)	(0.036)	(0.049)	(0.043)	(0.030)	(0.032)	(0.045)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Time Period	1790s	1800s	1810s	1820s	1830s	1840s	1850s	1860s
Obs.	93	93	93	93	93	93	93	93
R2	0.824	0.817	0.827	0.839	0.834	0.840	0.824	0.822

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors in parentheses clustered by closest climate point. All regressions are OLS. The dependent variable is log light density. All regressions include a constant. Controls are absolute latitude, longitude, the number of raster light density points within 500km of the port, dummies for AEZs, distance from the nearest Atlantic or Indian Ocean port of slave demand, and average temperature over the period 1902-1980. Additional controls are distance from the national capital, distance from the nearest foreign border, petroleum, and malaria suitability.